COMMUNICATION DEMAND IN THE NATIONAL AIRSPACE – A FEDERATED LEARNING APPROACH

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Abstract

Within the national airspace system (NAS), efficient use of spectrum remains a challenge; as UAS and UAM missions evolve, the amount of mission-critical aircraft communications are expected to significantly grow. To accommodate the increased demand, NASA Glenn Research Center is investigating artificial intelligence approaches that could dynamically allocate spectrum; however, these solutions are driven by communication and aviation data items, many of which are not directly available. One such cornerstone data item is communication demand, parameterizing the needs within a sector in terms that may directly inform spectrum allocation, such as channel access duration, bandwidth, and modulation type. This paper considers the complexity of predicting communication demand as a function of NAS behaviors. Unlike prior prediction work in communications, this research must consider how the NAS may be impacted by external factors - such as convective weather and closures - rather than estimating demand from time-series forecasting alone. Much of this research considers a federated learning design to predict communication events in terms of the type of event occurring (sector coordination, conflict resolution, etc). To do so, an investigation of products from Sherlock Data Warehouse is conducted, identifying the trends, sufficiency, and correlations of each product to identified events. Additionally, a preliminary discussion for inferring associations between these event types and their communication parameters (duration, bandwidth, modulation) is presented. By utilizing federated learning, imbalances in the types of events and data present throughout the NAS can inform local models without impairing global training. Furthermore, the two-stage approach proposed allows for robust and speculative communication modelling, as communication techniques continue to evolve. As a result, this model enables a generalized approach to understanding NAS communications which is able to inform long-term changes to aviation spectrum management.

Introduction

As airspace activities and technologies continue to develop, there exists a growing pressure to efficiently use and share communications resources, namely spectrum. Known as the spectrum scarcity problem, this challenge is thoroughly discussed regarding cellular and commercial wireless applications; in recent years, the challenge has become significant to the use of aeronautical spectrum as well. With approximately 14% of spectrum in the United States allocated to aviation purposes, the Federal Communications Commission and other regulatory bodies are especially interested in more efficient use of aviation spectrum [1]. This problem is exacerbated with evolutionary aircraft, such as Urban Air Mobility and Unmanned Aircraft Services, which will both require unique communications resources and are anticipated to proliferate the NAS in coming decades. To further complicate the issue, much of the NAS relies on legacy communications techniques, including static voice channels dedicated to specific sectors of the airspace.

As part of NASA's Transformative Aeronautics Concepts Program, Glenn Research Center is investigating methods of supporting dynamic spectrum allocation. This project specifically is interested in machine learning-based resource management solutions, which has the potential of providing flexibility and robustness in aircraft communications. In order to accomplish these approaches, a number of data items must be developed – including forecasts of airspace and spectrum resources and requirements.

This paper develops a concept overview of a two-phase, federated learning approach for predicting communication demand, where demand is predicted in terms of events affecting spectrum access which are used to infer parameters of spectrum utilization (e.g. bandwidth, access duration). Primarily, this research focuses on the first phase - event prediction - due to the degree of data complexity and significance associated with this portion of research.

This paper begins by summarizing existing areas of demand prediction, airspace workload, and federated learning to contextualize the goal of this concept. Following this, the stages of the concept research are presented: a high-level discussion of the framework, investigation of candidate data sources, a framework for predicting individual communication events, and a framework for inferring communication parameters from those events. Finally, conclusions are drawn.

Background

A literature review was conducted to cover demand prediction across a breadth of fields; predictive research analogous to the challenges within airspace demand prediction; and controller workload monitoring for improved NAS sectorization. Each topic was found to be adjacent to the challenge of demand prediction for aeronautical communications; however, few if any of the topics directly correspond to the challenges of this task.

Demand prediction is often investigated in a variety of applications, albeit more directly. In most research, resources such as spectrum [2], computing resources [3], electrical power [4], or taxi services [5] are predicted purely by anticipating seasonalities in data. Models vary between moving-average, stochastic, and deep learning approaches, but all rely on a purely time-series forecast, where prior observations dictate future predictions within the same data. Due to the complexity of NAS operations and availability of data to describe these operations, this class of approach provides limited relevance to the task of NAS demand prediction.

Significant research has addressed forecasting from a set of associated factors, specifically in the fields of cellular mobility prediction and medical computer-aided diagnosis. Surveys of mobility prediction are presented in [6] and [7], indicating the use of multiple potential features (current position, prior associations, prior Received Signal Stength measurements, road layouts) to predict either user movement or future cell associations based on deep learning and data mining techniques. Within the field of medical diagnosis, research using electronic health records to detect and predict health conditions such as heart disease provide an analogous problem formulation and approach to what may be encountered with NAS demand prediction [8].

Sufficiently modelling communication demand within the airspace requires a firm, working definition of communication sources. Research into airspace sectorization has developed a somewhat-transferrable understanding based on air traffic controller (ATC) workload modelling. Initial definitions of a holistic workload are provided in [9], which describes workload associated with monitoring, conflict detection, coordination, and altitude changes. This framework is expanded and rigorously defined in [10]. Additional sectorization work has applied these workload descriptions to define inherent safety and control costs [11], as well as optimize sector workloads during traffic flow management related to convective weather within a region [12].

In recent years, federated learning has offered significant benefit to distributed and complex classification, detection, and prediction research. In summary, federated learning assumes multiple clients train a structurally-identical model, periodically aggregating model parameters to effectively learn a more globally-accurate model. Federated learning has been directly applied to support incumbent access detection within evolving Citizens Broadband Radio Service research [13]. Beyond this, significant steps have been taken to generalize the usefulness of federated learning. The Astraea framework provides an effective method of training federated learning models on data with significant (non-IID) imbalances across client models [14]. Hierarchical approaches to federated learning allow the efficient aggregation and development of a global model without the communication overhead and delay of aggregating all clients to a central server [15].

Finally, federated learning is extended by the notion of personalization, where each client model balances global training via federated learning with an amount of local training or knowledge. These approaches are summarized in [16] and notably include the incorporation of client-specific data, applying local transfer learning to global models on distribution, weighting the optimization steps of a deep learning model as a balance of local and global updates, and splitting the model into a global (federated) and local (client) model portions.

Demand Prediction Framework

The remainder of this paper describes a concept for estimating the communication demand and spectrum utilization within the NAS, such that resource allocation can be performed with sufficient notice for continuity of operations. This section serves to define the key requirements and architecture of demand prediction.

Initial autonomous spectrum allocation concepts posited several key requirements and constraints that are integral to research and development [17]. Of the challenges described, the following are considered relevant to demand prediction work:

- **Data Engineering**: the effective application of any machine learning technique relies on effective data identification, feature selection, filtering, and preprocessing. For demand prediction, it is key that the sufficiency of selected data be established.
- **Technology Implementation Independence:** any autonomous allocation approach should be applicable regardless of the underlaying radio communication system. Consequently, any demand prediction work must account for potential difference in communication requirements for similar demand scenarios.
- **Backwards Compatibility:** allocation approaches should not disrupt existing aviation communication systems and operations. While prediction work will not disrupt airspace operations, it must account for the presence of both new and legacy communication techniques.
- **System Resiliency:** allocation approaches must support safe airspace operation under the event of facility outages, limitations, and other external hinderances to the NAS. Prediction work must therefore account for many of the most common sources of capacity limitations when prescribing airspace demand.

Additionally, a hierarchical approach to both prediction and resource management is described in the initial concept based around the scope of airspace control:

- At the national level, predictions are aggregated to determine broad controls such as a frequency reuse factor and broad spectrum bands for each airspace region.
- At the regional level, actual demand prediction for aggregate traffic flow and sector demand is performed. Based on this demand and ATCSCC allocations, sets of candidate channels are allocated to individual sectors and centers.
- At the sector and center levels, predictions are performed in granular scale based on live flight and weather information. Combined with regional predictions and controls, a joint channel-power allocation can be made to optimize spectral efficiency.

Inspired by the long-term scenario development in [18], this work attempts to modularize the prediction effort. The nature of an autonomous spectrum project is transformative for the NAS, and is likely to take decades before reaching test phases and physical implementation. In this time, spectrum policies may shift the nature of some airspace communications – further subchannelization or digitization of current air-ground control communications, for example. Anticipating this, the model separates prediction efforts into two phases.

The first phase considers the identification, correlation, and prediction of NAS events which currently require communications. For the scope of current research, events focus on those related to commercial airline activities which require communication and/or coordination between aircraft and an air traffic controller – predominantly within the 107-137 MHz spectrum band. Incorporation of communications related to flight dispatchers may be considered in the future, though is beyond the immediate scope of this formulation.

The second phase works to infer communication parameters – specifically (channel access duration, bandwidth, data rate, power, and modulation technique) – from the aggregate event predictions of a sector. As a necessity to accommodate demand prediction and simulation over the course of autonomous spectrum research, this inference must be generalized, such that current and speculative communication schemes might be modelled from event data.

For prediction efforts to effectively scale across NAS sectors – in terms of data behaviors, accuracy, and real-time operation – model designs must consider the application of federated learning. Trends in NAS events vary significantly from one sector to

another. This variance poses a challenge to prediction efforts: while global relationships and trends still must be learned to effectively correlate available data to communications, a degree of model personalization may be necessary in order to capture the needs resulting from sector-specific complexities.

Data Investigation

This section presents a thorough discussion of available data sources for the representation and prescription of communication demand within the NAS. Discussion first centers an understanding of demand sufficiency based on ATC workload monitoring; following this, candidate data sources available via NASA's Sherlock Data Warehouse (SDW) are described and associated with workload models. Finally, data sources are considered which may provide insights into communication parameters associated with each airspace event.

Workload Monitoring

Based on research in [9] and [10], communication events are described in terms of four categories:

- **monitoring workload**, where a baseline workload is ascribed to sectors by their current airspace density and average transit time; this workload is heavily informed by airspace density and sector transit time.
- **coordination workload**, representing the processes of transferring aircraft between sectors and airspace classes.
- **conflict resolution workload**, where aircraft are assigned new routes, altitudes, and airspeeds to maintain a minimum separation between one another; conflicts are separated by the vertical (constant, climbing, descending) and horizontal (using the same, intersecting, or reciprocal airways) movement of each aircraft involved.
- and **maneuvering workload**, where aircraft are assigned new routes, altitudes, and airspeeds to mitigate external factors such as convective weather.

The combination of these four workloads serves as a basis to accurately describe the complexity and challenges dealt with by air traffic controllers – a central user and holistic representation of aeronautical communications within any given sector.

Summary of Sherlock Data Sources

Candidate data sources are summarized in Table 1, describing the types of data available and relevant workload portions represented by each source. Additionally, Figure 1 maps each relevant data item to model inputs and outputs by workload type.

Flight-Level Information

Most significant for generating label data are Integrated Flight Format (IFF) and Flight Event (EV) files. Both provide complete information related to each flight within the NAS over the course of a day. A granular level of detail is provided by both files, which must be aggregated and reformatted to be applied in model training.

Aside from live flight track positioning, IFF data provides flight plan information, including initial filings, amendments, re-broadcasts, and irregular communications associated with flight ascent and descent phases. Consequently, this information is key to deterministically representing the most crucial forms of communications surrounding conflict detection and aircraft maneuvering. This information can be directly tied to the sector in which a radio communication occurs due to available message destination information.

EV data, on the other hand, tracks routine flight occurrences and phases, such as altitude changes, ascent and descent, sector crossings, takeoff/landing, and go-around events. Each of these events is a key aspect of routine aircraft communications, describing a great deal of aircraft maneuvering and coordination. Because of available sector crossing information, EV data may be easily localized.

Sector-Level Information

Sector-level information – made available by daily sector statistics and regular instantaneous aircraft counts - provides key inputs and labels for communication event estimation. These data are collected for all sectors within a region.

Sector statistics contain valuable summary data of airspace activity and flow. Statistics include total aircraft counts and sector transition matrices; hourly sector flows; and average transit time, distances, and airspeeds. Supplemented by instantaneous sector aircraft counts, these statistics provide a foundation for predicting monitoring and routine coordination workloads within each sector.

Table 1: Summary of Investigated Sherlock Data Sources

Dataset	Summary	Workload Sufficiency
IFF Data	Flight plan amendments (route, airspeed, and altitude changes), re-broadcasts, and flight track information	Coordination: re-broadcasts indicate sector crossings Conflict detection: amendments Aircraft maneuvering: amendments
EV Data	Flight events in terms of airspace operations: Takeoff/landing, top-of-climb / descent, sector crossing, go-around, etc.	Aircraft Maneuvering: Altitude changes described in-detail Coordination: sector crossings Conflict detection: go-arounds and altitude changes
Instantaneous Counts	Sector aircraft counts over 15-minute windows: Min, max, average, aggregate	Horizontal Movement: sector density
Sector Statistics	Daily statistics of each sector: Total aircraft count, hourly flow, Average transit time and airspeed, Sector transition counts	Horizontal movement: average transit time, density statistics Coordination: Sector transition counts
NOTAMs	Urgent, non-standard conflicts and airspace outage notices	Conflict Detection: indication of reduced sector / center capacity
CWAM	Describes regions with high probability of convective weather (60/70/80%)	Aircraft Maneuvering: adjusted airflows from convective weather
Echo Top	Radar measurements of cloud height, corresponding to convective weather severity	Aircraft Maneuvering: adjusted airflows from convective weather

Airspace Resiliency and Adjustment Information

Finally, representation of capacity limits and NAS continuity-of-operations work are accomplished with a combination of Notices to Air Missions (NOTAMs) and convective weather information provided by either NASA's Convective Weather Avoidance Model (CWAM) or Echo Top measurements. These data sources inform displacements in air traffic flow, existing workloads, and consequent workloads related to conflict detection.

NOTAMs provide an airspace-wide report of facility outages and sector limitations such as limitations on runways, navigation systems, and other airspace hazards. Such information is often filed ahead of the event's actual occurrence, making it possible for traffic flows to be displaced according to the type of restriction presented.

For other traffic management changes where airspace-wide restrictions may not be applicable, convective weather information remains key. Echo Top, a radar measurement of cloud height, has strong correlation to convective weather severity, is regularly updated (every 2 ½ minutes), and provides continental coverage; existing aircraft trajectory prediction research utilizes this measurement heavily, though significant preprocessing is necessary due to its scope and size. Conversely, SDW provides a statistical model, CWAM, which dynamically defines regions of airspace with a high probability of air traffic rerouting due to convective weather. Both data items may be key supplements to recognizing airspace capacity limitations, though localization and other preprocessing tasks may restrict the real-time capabilities of prediction work.

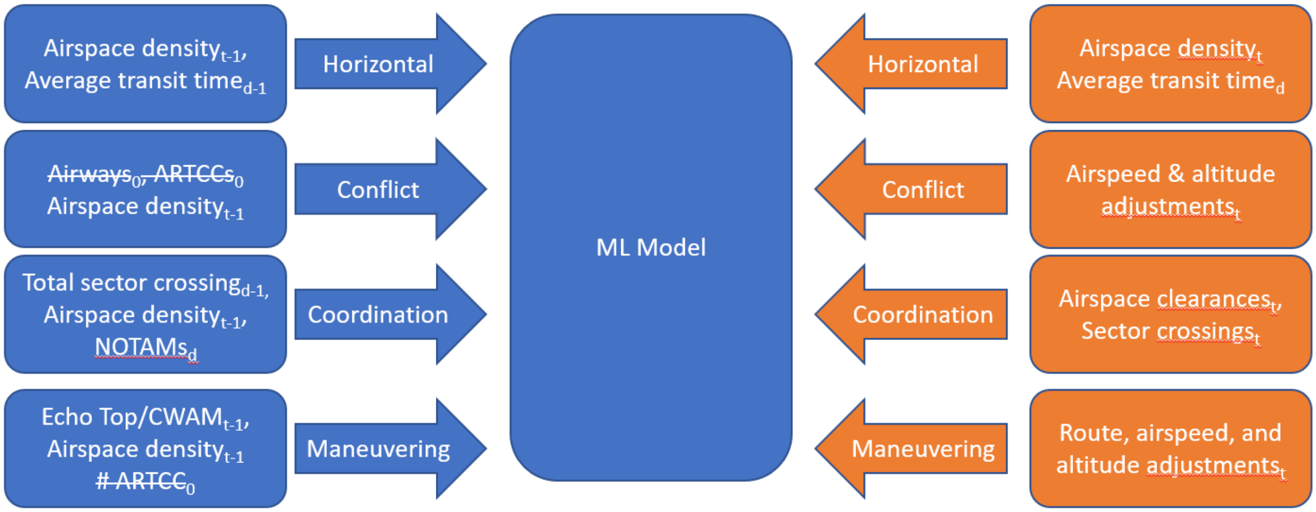

Figure 1: Application of Relevant Data Items by Workload Type

Figure 1 describes the mapping of specific data measurements as either inputs (left) or labels (right) according to the type of related workload. The time-scale of each data item are referenced either as static (item$_0$), lasting a day (item$_d$), or lasting a more limited timeframe (item$_t$). As noted in Figure 1, several key data items (struck through) may not be directly available or represented within event prediction work. Namely, this information provides context specific to the sector, including the number and structure of airways and centers. Prior research into airspace sectorization emphasizes the imbalance of sector workload and complexity; this structural information emphasizes why and how such imbalances are present, and therefore is necessary to model complexity. However, the amount of contextual sector-specific information is limited. As a result, federated learning personalization techniques are necessary to accommodate these gaps in data.

Communication Parameter Information

While the inference of communication parameters may be speculative for future technologies and communication standards, an undeniable necessity is that of approximating current parameters from available data. Many current communication parameters (bandwidth, transmission power, modulation technique) are statically defined by ICAO standards. However, voice communications related to advisories and flight adjustments are likely to vary in duration significantly as a result of the nature of the communication. For this reason, it becomes key to identify communication data which may be available to support parameter inference.

Directly available and incorporated in workload monitoring, NOTAM messages also provide select parameters, such as the channel in which a message is broadcasted and duration of the broadcast. As a result, advisory message parameters may be directly inferred.

The availability of such communication data for clearances, requests, and adjustment procedures, however, is much clearer. Records of such information are maintained as Controller-Pilot Data Link Communications (CPDLC) messages, though the availability of such data poses a challenge. Direct monitoring of spectrum may accommodate challenges of availability, instead requiring significant data collection and processing efforts.

Communication Event Prediction

Event prediction – covering the largest modalities of data and complexities of relationships – proves the greatest challenge to define. To reinforce the hierarchical approach to resource management and prediction in [17] and to verbosely incorporate the data relationships anticipated by NAS operations, event prediction is broken into three categories of work.

- **Aggregate Prediction**, where sector-level estimations of demand are generated based on trends in sector-level data;
- **Discrete Prediction**, where live flight and weather information are used to learn and forecast exact coordination, maneuvering, and conflict resolution workloads;
- and **Relational Prediction**, where resiliency and adjustment information are provided at the regional level to inform workload displacements.

Summarily, these prediction approaches and their interactions are represented in Figure 2.

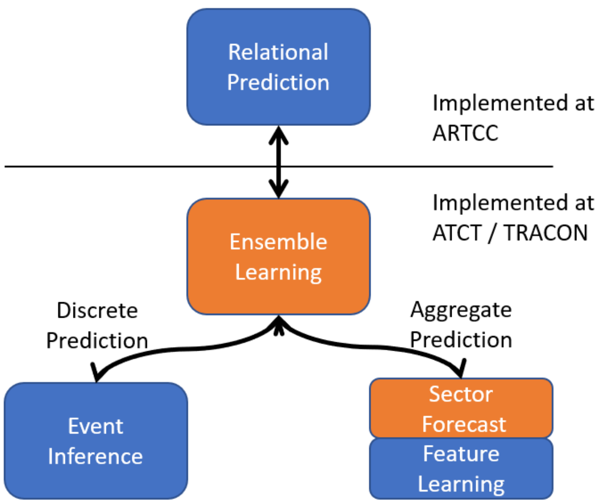

Figure 2: Interactions of Event Prediction Objectives

Aggregate Prediction

Aggregate Prediction focuses on the forecasting of approximate demand levels using prior information and relevant statistics. This approach focuses heavily on learning the relationships and trends of data – how changes in airspace density, for example, impact coordination and conflict resolution workloads. Within this prediction work, models are developed at the sector level.

To effectively generate these predictions, data must be constrained to nominal airspace conditions. Airspace and center conditions should be limited during this training, such that NOTAMs and severe convective weather are not present, then balanced to insure certain times of day or other seasonalities are not disproportionately represented.

For this task, federated learning is proposed as a method of leveraging a common goal and data items across each sector model. However, the complexity of sector workloads varies greatly, not only because of airspace density and frequency of access, but also due to variances in the inherent structure (number and layout of airways and centers) of each sector. For this reason, a direct application of federated learning is not sufficient and personalization techniques are required. Federated personalization – the development of client models with unique parameters, while still leveraging federated learning to globally train each client - is summarized in [16]. Approaches to incorporate personalization may include:

- Adding sector-level context: generating innate sector statistics (number of airways, airway intersections, centers, center size) may be possible, given appropriate data availability.
- Separate global and personalization models / layers: developing a deep learning model, such that initial layers extract features and feature relationships may provide a functional and explainable approach to demand prediction.
- Transfer learning: developing only a global model, which is then briefly supplemented with training at the client level to become better-suited to available local data.

Additionally, imbalances in the levels of workload across sectors may impact the training of a global models. Accommodating this can be accomplished by application of regional mediators, similar to that of the Astraea framework [14]. These mediators would selectively aggregate sector models and parameter updates based on the known workload distribution, limiting the chance of biases in federated training rounds as a result. This implementation, however, may prove challenging. The original Astraea framework was applied to image classification, where data were balanced in terms of a single, discrete class label; for demand prediction, data workloads vary continuously across multiple

dimensions, consequently requiring a massive collection of data to appropriately balance training.

Due to the scale of prediction work envisioned – operating at the national, regional, and sector-level – federated learning approaches must be implemented hierarchically. Traditional approaches to federated learning consider a set of client (sector) models aggregating parameters at one central (national) server, requiring significant communication overhead to achieve. Alternative approaches place federated servers at edge devices (region), improving training speed, responsiveness, and overhead at the cost of a reduced set of clients – hindering the total model accuracy. Hierarchical federated learning, as discussed in [15], proposes a combination of the two: by splitting the total set of federated aggregations into a ratio of edge and central aggregations, federated learning models are able to maintain the large clients (and data) with limited overhead and faster model convergence.

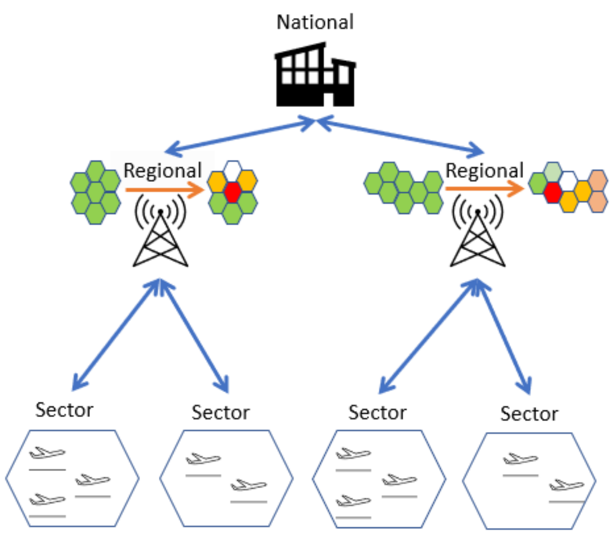

Figure 3: Hierarchical Approach to Communication Event Predictions

Discrete Prediction

Discrete prediction aims to detect workload at a granular level within each sector, predicting each workload aspect for individual flights based on their prior position and movement information, as well as local convective weather information.

By predicting with live, discrete flight information, it is anticipated that workloads can be more precisely described. From there, predictions relating to each aircraft can be aggregated to determine sector-level demand. While this approach may detect certain communication demand events precisely (i.e. conflict detection, directly related to aircraft spacing), it is anticipated that inference at this level may suffer limitations of data, where communications such as altitude changes and requests to operate according to visual/instrumental flight rules.

Because of the level at which data is predicted, it is unlikely that the formulation for discrete prediction would be impacted by facility outages and other resiliency challenges. Even so, the approach is artificially restricted to nominal conditions, such that the scope of conditions are identical to that of aggregate prediction.

Because of the scale at which data are presented, federated learning of each discrete prediction is expected to benefit greatly from federated learning. Similar to aggregate prediction, a hierarchical federated learning approach is proposed, based on HierFAVG [15]. Personalization may be necessary in limited amounts, specifically by providing sector boundary information to client models.

Ensemble Learning

In discussion of event prediction under nominal conditions, two approaches have so-far been discussed. Aggregate prediction, while holistic, is anticipated to provide approximate demand forecasts; discrete prediction, while limited in scope, may provide more precise forecasts. Ensemble learning is included here as a method of incorporating and weighting the usefulness of each method's predictions, such that a more accurate prediction of demand can be achieved. Prior research has used these techniques to balance and select between complementary deep learning models for estimating taxi demand in cities [5] and detecting heart disease from patient health records [8].

Relational Prediction

Based on the output of the referenced ensemble learning method, an effective prediction of airspace communication under nominal conditions is provided. From here, relational prediction serves to approximate the displacements in demand across sectors in a given region.

Each relational predictor is implemented at the regional level. Following prior research into airspace density prediction, the approach to relational prediction may be restricted as a conservation-of-flow problem. Consequently, while deep learning approaches may function, explainable machine learning models may be possible and preferrable.

For this prediction objective, federated learning is ignored. Each region has a unique structure (number and layout of sectors, number and layout of airways), and therefore would require significant personalization to apply any federated learning approach. Given the relative simplicity of this objective and limited number of airspace regions, federated learning is considered unsuitable.

Parameter Inferencing

As communications evolve, communication parameters must be inferred or prescribed according to the technologies in-use – whether currently or in speculative scenarios. In both cases, parameters (channel access duration, bandwidth, data rate, power, and modulation technique) must be determined by the level of communication for each type of workload within the prior event predictions.

To infer communication parameters based on current airspace operations requires varied amounts of data. Many of the parameters (bandwidth, data rate, transmit power) are fixed according to current ICAO standards, dependent on the type of communication event occurring. A model becomes necessary, however, to represent channel access durations associated with each event, where a significant variance in time is possible for advisories and clearances procedures over voice channels.

Similarities between events may be identified via a number of machine learning techniques. K-means clustering has been previously used to associate activity levels of land mobile radio bands with real-world events, and as such may be applicable for this situation [19]. Other approaches may include naïve and explainable machine learning techniques such as K-nearest neighbors or linear regression models. Depending on the distribution of data, a hierarchical federated learning approach may be recommended to unify communication patterns across sectors.

Speculative analysis may be defined as a system of equations, with assumed parameter weights. Once again, channel access duration is the only parameter which may vary significantly, requiring a machine learning approach. This duration information may be transferred from prior inferencing using NOTAM and (if available) CPDLC data.

Conclusion

Aviation spectrum remains a finite and heavily-constrained resource. Approaches to optimize spectrum allocation consider machine- and deep-learning techniques, enabling flexibility of operations; however, supporting these approaches requires the development of clear data products, particularly to represent communication demand as an informing requirement for optimization. This paper defines a robust concept for estimating communication demand within the NAS by assessing the range of communications in terms of air traffic controller workload. Prediction work is broken into two stages – event prediction and parameter inference – in order to modularize demand prediction in support of current and speculative communication scenarios. Event prediction considers the cohesion of multiple learning objectives, such that data at each level of airspace operation may be leveraged to reflect both demand and airspace capacity limitations. This approach is expected to provide a framework for developing key data inputs in resource optimization, and will be implemented in future work.

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